International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 9, No.4 (July-2020)

http://dx.doi.org/10.12785/ijcds/090404

Qualitative and Quantitative Performance Comparison of ECG Noise Reduction and Signal Enhancement Method based on Various Digital Filter Designs and Discrete Wavelet Transform

Thion Ming Chieng[1], Yuan Wen Hau[2], Zaid Bin Omar[3] and Chiao Wen Lim[4]

[1, 2]UTM-IJN Cardiovascular Engineering Centre, School of Biomedical Engineering and Health Sciences, Faculty of Engineering, Universiti Teknologi Malaysia, Johor Bahru, Johor, Malaysia.
[3]School of Electrical Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, Johor Bahru, Johor, Malaysia.
[4]Faculty of Medicine, Universiti Teknologi MARA, Sungai Buloh, Selangor, Malaysia.

Received 6 Jan. 2020, Revised 12 Apr. 2020, Accepted 11 May 2020, Published 1 July 2020

Abstract: Electrocardiogram (ECG) is a graphical representation and bio-signal recording of cardiac electrical activity. It conveys a great amount of information regarding structural and functional performance of the heart. Hence, ECG plays an essential role in the cardiac assessment, abnormality detection and clinical diagnosis. A clean ECG signal plays an imperative and vital role in the primary clinical analysis and diagnosis of cardiac diseases. Unfortunately, the greatest obstacle in analyzing and interpreting an ECG signal is the presence of unwanted artifacts and noises as they contaminate and degrade the quality of the ECG signals. As a result, removal of unwanted artifacts and noises from an ECG signal becomes an indispensable task to ensure an accurate and reliable ECG analysis could be performed. In this study, many ECG noise reduction and enhancement methods based on various digital filter designs, as well as discrete wavelet transform with various mother wavelets, are modelled to investigate and benchmark their performance in term of Signal-to-Noise Ratio (SNR) and Root Mean Square Error (RMSE). This testing are based on ten randomly selected ECG datasets acquired from ECG-ID Database (*ecgiddb*) which available in PhysioNet. Based on structured qualitative and quantitative performance analysis, results conclude that the discrete wavelet transform with db8 as mother wavelet outperforms the Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) digital filter designs in de-noising and enhancing a raw ECG signal with highest SNR value of 4.4148, at the same time achieve significant lowest RMSE value of 4.0767. This is due to the reason that discrete wavelet transform method has advantages in analyzing the ECG signal in both time and frequency domain, thus causing less distortion to ECG signal.

Keywords: Cardiovascular diseases, Digital filter designs, Discrete wavelet transform, Electrocardiogram (ECG), Noise reduction and enhancement, Mother wavelets function.

1. Introduction

According to the World Health Organization (WHO) in 2016, an estimated 17.9 million people died due to the cardiovascular diseases (CVDs), which occupied about 31% of all causes of deaths [1-3]. CVDs refer to a class of malfunction or diseases that related to the heart and blood vessels, such as coronary heart disease, cerebrovascular disease, peripheral arterial disease, rheumatic heart disease and congenital heart disease. These can cause acute and deadly cardiac events, for example heart attacks, strokes, arrhythmias and sudden cardiac death. Among these deaths, approximately 60% occurred outside of the hospital [4]. In addition, over three quarters of CVDs deaths occurred in low- and middle-income countries [5]. Hence, it is vital to highlight the severity of this worldwide health issue and more attention should be paid to investigation of computerized CVDs detection, prediction and diagnostic approach that able to assist the cardiologists in saving the patient's life.

Electrocardiography is an established non-invasive diagnostic tool which is widely used for screening, observing and recording the electrical activity of the heart. The electrical activity of the heart is represented by a biosignal, so-called Electrocardiogram (ECG), by measuring the potential difference between the leads or electrodes attached on the surface of the body. In other words, ECG signal is a graphical representation of the electrical changes that arise from the contraction of

E-mail: billy5392@gmail.com, hauyuanwen@biomedical.utm.my, zaid@fke.utm.my, chiaowen.lim@gmail.com

myocardial muscles in initiating the cardiac depolarization and repolarization process. Thus, ECG conveys a great amount of information about the structural and functional performance of the heart as well as to identify cardiac abnormalities and diseases [6, 7]. It plays an essential role in the cardiac assessment, abnormality detection and clinical diagnoses.

However, an ECG signal is inexorably corrupted and degraded by several noise sources during ECG acquisition and transmission process. This cause a huge complication in analyzing and identifying the ECG abnormalities [8]. ECG noises that commonly encountered includes powerline interference [9-13], baseline wander [14-17], electromyography noise [18, 19], and electrode motion noise [20-26]. The ECG analysis can be challenging with the existence of these artifacts as the chance of misinterpretation increase, subsequently lead to the inaccurate clinical analysis and diagnosis result. Hence, it is crucial to reduce, suppress and eliminate the unwanted artifacts in a raw ECG signal while preserving the important ECG characteristics. As a result, ECG noise reduction and signal enhancement become an important and indispensable prerequisite task to ensure the reliability and accuracy of the following clinical analysis and diagnosis process is guaranteed. This task is never considered as a trivial procedure due to the nature non-stationary characteristics of an ECG signal, and the noises might lie within the similar frequency spectrum range with the significant ECG characteristics feature. Thus, an effective ECG noise reduction and signal enhancement approach is essential to achieve satisfactory noise reduction performance while maintaining minimal loss of noteworthy ECG features.

Through the topic of ECG noise reduction and signal enhancement has been widely studied and well-established, to the authors' best knowledge, there is no literature reported comparison between different digital filter designs and discrete wavelet transform with different mother wavelet functions using structured approach for systematic benchmarking in this topic yet. This article is an extension of work reported in [27] which aims to explore various aforementioned ECG noise reduction and signal enhancement techniques using systematic quantitative and qualitative approach based on standard dataset for fair comparison and benchmarking. This article also briefly discusses the ECG morphology and the characteristics of the ECG noises that frequently encountered with.

This article consists of seven sections which begin with an introduction of ECG and its challenges in ECG analysis. Section 2 briefly describes the future trends in ECG de-noising and enhancement based on comprehensive literature review. The basic morphological characteristics of the ECG are briefly described in Section 3. Section 4 presents the theoretical knowledge of various digital filter designs which includes FIR and IIR filters. Section 5 presents the discrete wavelet transform and wavelet decomposition method with various mother wavelets. The methodology of comparing and benchmarking of ECG noise reduction and enhancement methods based on several types of digital filter designs and mother wavelets are presented in section 6. Section 7 presents and discusses the experimental result and performance benchmarking of various noise reduction methods based on common dataset. Lastly, section 8 concludes the whole finding.

2. FUTURE TRENDS IN ECG DE-NOISING

Over the last decades, there have been a rapid advancement in big data analysis, artificial intelligence, deep learning and machine learning, in various fields including biomedical signal processing research. This phenomenon has also been extended to the fields of ECG signal pre-processing and de-noising which enables an accurate, precise and significant information to be provided to clinicians with greater insights for decision making within short periods of time. Besides that, an effective and efficient ECG de-noising and filtering method are extremely crucial especially for those portable and wearable ECG devices for remote or continuous heart monitoring. A raw ECG signal that acquired by these devices was normally contaminated by a lot of unwanted noises, especially electromyogram (EMG) and electrode motion noise. Electromyogram and electrode motion noise are the ECG noises difficult to be filtered or removed by conventional de-noising approaches. Hence, the emerging machine learning and deep learning based on neural network would be future trends in ECG de-noising and filtering. There are few ECG filtering and de-noising algorithm based on different structure of neural network have been proposed in the most recent literature which would be briefly discussed in this section.

In 2016, Xiong *et al.* [28] proposed a novel deep neural network (DNN) method to de-noise and eliminate the noises that manifest with ECG morphology waveform in the frequency domain. The DNN-based de-noising technique is created based on an improved de-noising auto-encoder (DAE) which reformed with the wavelet transform method. The wavelet based adaptive thresholding method will first eliminates most of the ECG noises and artifacts, followed by the improved DNN-based DAE to remove and eliminate the remaining complex ECG noises and artifacts with unknown frequency distribution. The proposed method was evaluated by the ECG recording acquired from the MIT-BIH Arrhythmias Database, whereas the noise and artifact signal were obtained from the MIT-BIH Noise Stress Test Database. The proposed novel DNN method obtained significant improvement and outperformed individual wavelet processing or de-noising auto-encoder method in terms of SNR and RMSE value. Hence, it proves a promising approach by applying a DNN model in ECG signal de-noising and signal enhancement. However, this approach demands a very comprehensive and carefully selected features as the learning DNN model is based on well-defined training samples [28].

Antczak [29] proposed a novel ECG de-noising approach based on a deep recurrent neural network (DRNN) by utilizing a transfer learning technique which pre-trained with the synthetic data. The synthetic data are generated by a dynamic ECG model and fine-tuned with the real ECG data. The proposed DRNN method contains two distinct features which consist of multiple layers stacked together and able to preserve its internal state over time. The proposed ECG de-noising method based on four-layer deep recurrent neural network outperforms the reference methods that based on the bandpass filter and undecimated wavelet transform (UWT) methods. It was tested and evaluated on the real ECG dataset with various amounts of noise. The experiment results show that DRNN based de-noising method obtains effective 7.71 dB SNR from the input signal over -8.82 dB SNR produced by the reference methods [29].

Arsene *et al.* [30] have also proposed two deep learning models, which are convolutional neural network (CNN) and long short-term memory (LSTM), to de-noise and filter a raw ECG signal. There are three different datasets, which consists of two synthetic datasets and one real dataset were used to evaluate the performance of the proposed deep learning based ECG de-noising approach. The experiment results show that the CNN model is superior compared to LSTN model in terms of processing time and root mean square value and its capability in rejecting high level of ECG noises [30].

It could be foreseen that more artificial intelligence based ECG filtering and de-noising approaches are developed and proposed in the near future to allow the computational intelligent way to enhance and optimize the current ECG filtering and de-noising methods.

3. ELECTROCARDIOGRAM AND ITS MORPHOLOGY

In this section, the basic morphology of ECG is briefly presented. ECG is a graphical representation of cardiac electrical activity which provides significant information of the cardiac electrophysiological characteristics. Its frequency bandwidth is ranging from 0.05Hz to 100Hz, yet the significant features are mainly located between 0.5Hz to 45Hz with greatest possible peak amplitude of 1mV [31-33].

A typical ECG signal consists of several basic morphological features, so-called P-wave, QRS complex, T-wave and U-wave as shown in Figure 1 [34]. P-wave represents the atrial depolarization which occurs when the sinoatrial node firing electrical impulse and spread through the walls of atria and causing them to contract. The electrical impulse is then transmitted throughout the atria to the atrioventricular node, a cluster of cells in the center of the heart between atria and ventricles. The atrioventricular node delays the impulse by approximately 0.12 seconds to ensure the ventricles have enough time to be fully filled with blood [35]. This delay is denoted by the isoelectric line, PR segment just after the P-wave. The impulse is continuing to transmit from the AV node to the ventricles via His bundle, bundle branches and Purkinje fibers. These impulses cause the ventricles to contact and allows the blood to be pumped out from the ventricles and circulates into lungs and other parts of the body. This process, known as ventricular depolarization, is denoted by the greatest deflection, so-called QRS complex.

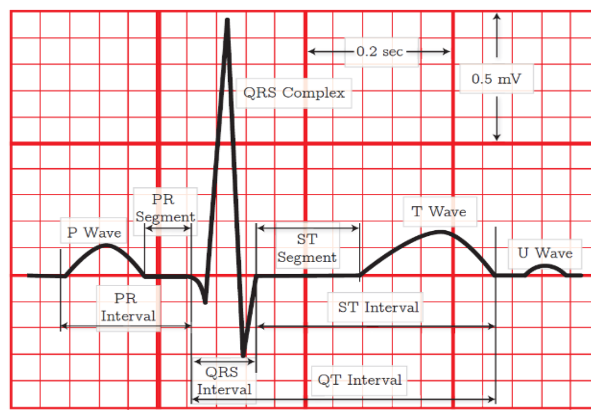


Figure 1. ECG waveform of healthy adult [34].

The QRS complex is then followed by an isoelectric line, known as ST segment. It is located between J point and T-wave, which results from the long plateau period of myocardial cells. It represents the interval between ventricular depolarization and ventricular repolarization process. Ventricular repolarization is the recovery or relaxation process of ventricular muscle which denoted by T-wave. Additionally, U-wave may appear or visibly after the T-wave, but not always. The cardiac cycle end with the sinoatrial node firing another new electrical impulse.

These ECG morphological features are highly significant as the right understanding and accurate interpretation allows the identification of various cardiac malfunctions and abnormalities. As a result, it is essential to reduce, suppress and eliminate noises from an ECG signal to allow accurate clinical interpretation and avoid misdiagnosis of the cardiovascular diseases.

4. DIGITAL FILTER DESIGNS

Digital filter is a system which computes mathematical operation on a discrete and sampled time signal with the purpose of enhancing and improving certain aspects of the signal. It is different with the conventional analogue filters as it uses finite precision to represent signals and coefficients, as well as finite precision arithmetic to compute the filter response. The basic method of implementing a digital filter is by performing convolution to the input signal with the impulse response of the filter, or multiply the signal with the frequency domain impulse response of the filter. Digital filters can be categorized into Finite Impulse Response (FIR) filter and Infinite Impulse Response (IIR) filter. Both FIR and IIR filters will be briefly described in the following subsection.

A. Finite Impulse Response (FIR)

The FIR filter is one of the basic elements in a digital signal processing system. It guarantees a strict linear phase frequency characteristic with any kind of amplitude frequency characteristic. As its impulse response is finite, it is a stable digital system [36]. FIR filter is a filter having a transfer function of a polynomial in z-plane and is an all-zero filter with no poles in the sense that the zeroes in the z-plane determine the frequency response magnitude characteristic. The system transfer function of the FIR filter is given as:

$$H(z) = \sum_{n=0}^{L-1} h(n) z^{-n} \tag{1}$$

where L is the length of the filter and $h(n)$ is the impulse response with finite duration N.

Windowing is one of the ways to design an FIR filter. The impulse response, $h(n)$, can be obtained by the product of $\{h_d[n]\}$ and a window function $\{w[n]\}$ as described in the following mathematical equation:

$$h[n] = \begin{cases} h_d[n], & N_1 \le n \le N_2 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$\{h[n]\} = \{h_d[n]\}\{w[n]\} \tag{3}$$

Some common windowing functions are described as follows:

1) Rectangular Window

$$w_R(n) = \begin{cases} 1, & 0 \le n \le N-1 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

2) Bartlett Window

$$w_B[n] = \begin{cases} 2n/(N-1), & 0 \le n \le (N-1)/2 \\ 2 - \frac{2n}{N-1}, & \frac{N-1}{2} \le n \le N-1 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

3) Hanning Window

$$w_{Han}[n] = \begin{cases} \frac{1-\cos\left[\frac{2\pi n}{N-1}\right]}{2}, & 0 \le n \le N-1 \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

4) Hamming Window

$$w_{Ham}[n] = \begin{cases} 0.54 - 0.46\cos\left[\frac{2\pi n}{(N-1)}\right], & 0 \le n \le N-1 \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

5) Blackman Window

$$w_{bl}[n] = \begin{cases} 0.42 - 0.5\cos\left[\frac{2\pi n}{N-1}\right] + 0.08\cos\left[\frac{4\pi n}{N-1}\right], & 0 \le n \le N-1 \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

6) Blackman-Harris Window

$$w_{BH}(n) = \begin{cases} w_R(n) \sum_{l=0}^{N-1} \alpha_l \cos(l\emptyset_M n), & 0 \le n \le N-1 \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

where $\emptyset_M \triangleq 2\pi/M$ and $w_R(n)$ is the length of zero-phase rectangular window.

7) Kaiser Window

$$w_K[n] = \begin{cases} I_0\{w_a[\left(\frac{N-1}{2}\right)^2 - (n - \frac{N-1}{2})^2]^{\frac{1}{2}}\}, & 0 \le n \le N-1 \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

where $I_0(x)$ is modified zero-order Bessel function, $I_0(x) = 1 + \sum_{n=1}^{\infty} [(\frac{x}{2})^n \frac{1}{n!}]^2$

There are several attractive characteristics of the FIR filters, such as simple to implement, inherently stable, easy to attain linear phase, simple extension to adaptive filter and relatively flexible to obtain the designs that match to custom magnitude responses [37]. However, FIR filter does have its limitations which include computationally expensive, long transient response and require large filter order to accomplish the task given.

B. Infinite Impulse Response (IIR)

IIR filter is the most efficient filter in digital signal processing. It is the digital filter with infinite impulse response and recursive structured filter with the feedback loop. The impulse applied to the filter with the response will never decays to zero due to its recursive design. Hence, IIR filter have better frequency response and relatively small delay compared to the FIR filters due to its shorter transient response. Unlike FIR filter, the phase characteristic of IIR filters is not perfectly linear [38]. The system transfer function of IIR filters and its frequency response are defined as below:

$$H(z) = \sum_{n=0}^{\infty} h(n) z^{-n} = \frac{\sum_{i=0}^{M} b_i z^{-i}}{\sum_{i=0}^{N} a_i z^{-i}}; \quad a(0) = 1 \tag{11}$$

$$|H(e^{jw})| = \left\{\frac{[\sum_{i=0}^{M} b(i)\cos(iw)]^2 + [\sum_{i=0}^{M} b(i)\sin(iw)]^2}{[\sum_{i=0}^{M} a(i)\cos(iw)]^2 + [\sum_{i=0}^{M} a(i)\sin(iw)]^2}\right\}^{\frac{1}{2}} \tag{12}$$

where at least one of the a_i or b_i is nonzero and the impulse response $h(n)$ must obey the following rules:

$$h(n) = 0 \quad n < 0\,; \quad \sum_{n=0}^{\infty} |h(n)| < \infty \tag{13}$$

There are four different basic and classic designs of IIR filters, known as Butterworth, Chebyshev type I, Chebyshev type II and Elliptic which will be briefly described in the following subsections.

1) Butterworth filter

Butterworth filter is a filter that characterized with the maximally-flat frequency response in the passband and stopband. The frequency response of the Butterworth filter is defined as:

$$|B(jw)|^2 = \frac{1}{1 + \left({}^{jw}\!/_{jw_c}\right)^{2N}} \tag{14}$$

where N is the order of the filter and w_c is the cutoff frequency.

The maximally-flat properties of the Butterworth filter cause the transition band to be very wide and does not have the sharp cutoff. The filter order, however, can be increased to reduce the transition width, which at the same time increases the sharpness of the transition as show in Figure 2 [39]. The frequency response can approach an ideal condition when the filter order approaches infinity. In addition, the Butterworth filter has the least amount of phase distortion among the IIR filters.

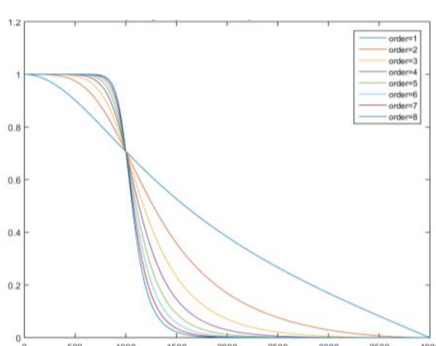


Figure 2. Frequency response of Butterworth filter [39].

2) Chebyshev type I filter

Chebyshev type I filter is a filter designed which allow ripples in the passband, and can attain a slightly shaper transition compared to Butterworth filter as shown in Figure 3 [39]. The frequency response of Chebyshev type I filter is defined as:

$$|B(jw)|^2 = \frac{1}{1 + \epsilon^2 T_N^2\left(\frac{w}{w_c}\right)} \tag{15}$$

where N is the filter order, ϵ is the passband ripple factor, and $T_N(x)$ is the N^{th} order Chebyshev polynomial given by:

$$T_N(x) = \begin{cases} \cos\left(N \cos^{-1}(x)\right), & 0 \le x \le 1 \\ \cosh\left(\cosh^{-1}(x)\right), & 0 \le x \le \infty \end{cases} \tag{16}$$

where $x = \frac{w}{w_c}$.

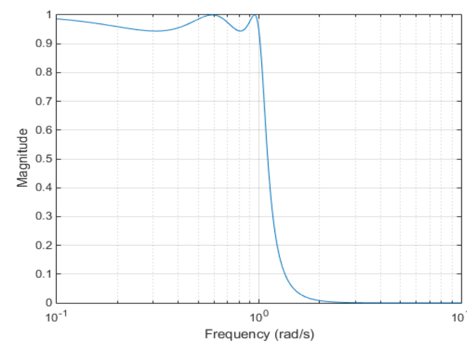


Figure 3. Frequency response of Chebyshev type I filter [39].

With the fixed filter order, the trade-off of Chebyshev type I filter is between the transition width and the amount of ripple or phase distortion.

3) Chebyshev type II filter

Chebyshev Type II filter, also known as inverse Chebyshev, is a filter design which allow the maximally-flat passband and the ripples in the stopband as shown in Figure 4 [36]. It minimizes the peak error in the stopband instead of the passband, which have the advantage of shaper transition between passband and stopband with a lower filter order when compared to Butterworth and Chebyshev Type I filter. The frequency response of the Chebyshev type II filter is defined as:

$$|B(jw)|^2 = \frac{1}{1 + \left[\epsilon^2 T_N^2\left(\frac{w_c}{w}\right)\right]^{-1}} \tag{17}$$

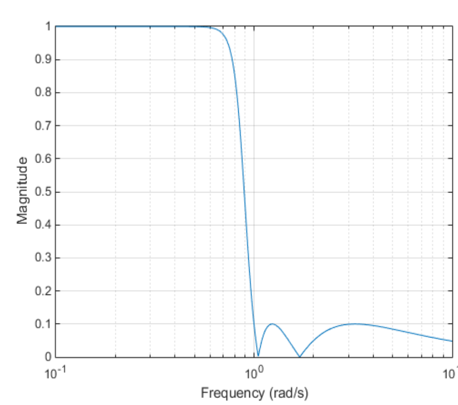


Figure 4. Frequency response of Chebyshev type II filter [36].

4) Elliptic filter

Elliptic filter, also known as Cauer filter, is a filter that generalizes both Chebyshev and Butterworth filters by allowing ripple in both passband and stopband as shown in Figure 5 [39]. The frequency response of Elliptic filter is defined as:

$$|B(jw)|^2 = \frac{1}{1+\epsilon^2 U_N^2(\frac{w}{w_c})} \quad (18)$$

where N is the filter order, ϵ is the ripple factor and U_N^2 is the N^{th} order Jacobian elliptic function.

The Elliptic filter can restrict the amount of ripples, and can achieve the minimum order of filter or sharpest transition band for the given specification with minimal phase delay. In other words, Elliptic filter is the optimal IIR filter that has smaller filter order to achieve the specification given when compared to other IIR filters.

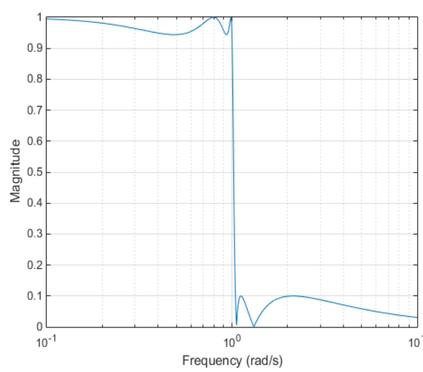


Figure 5. Frequency response of Elliptic filter [39].

5. Discrete Wavelet transform

Discrete wavelet transform is a robust multiresolution analysis of a signal in both time and frequency domain. It was first introduced by Mallat [40]. A wavelet is a small wave having the energy concentrated in time to allow the analysis of transient and nonstationary properties of a signal [41]. In other words, the discrete wavelet transform decomposes a signal into elementary frequency bands that localized in both time and frequency scales. The low frequency component does appear in high scale, whereas the high frequency component appears in low scale. In this way, discrete wavelet transform able to provide excellent time-frequency resolution [42]. Hence, it is an important and useful tool in the application of digital signal and image processing. Wavelet function, $\varphi(t)$ is defined in a space of measurable functions which are absolute and square integral as follows [42]:

$$\int_{-\infty}^{+\infty} |\varphi(t)| dt < \infty \quad (19)$$

$$\int_{-\infty}^{+\infty} |\varphi(t)|^2 dt < \infty \quad (20)$$

The wavelet function should satisfy the following conditions of zero mean and one for square norm as follows:

$$\int_{-\infty}^{+\infty} |\varphi(t)| dt = 0 \quad (21)$$

$$\int_{-\infty}^{+\infty} |\varphi(t)|^2 dt = 1 \quad (22)$$

The discrete wavelet transform of a function, $f(t)$ is described as:

$$Wf(a,b) = \int_{-\infty}^{+\infty} f(t)\varphi * \left(\frac{t-b}{a}\right)(t)dt \quad (23)$$

where a is the scale factor, b is the dilation or translation factor, and $*$ is the complex conjugation sign.

The wavelet transform realizes that the signal to be analyzed $f(t)$ is convolved with a dilated mother wavelet $\varphi(t)$. It is capable of signifying the signal in different resolution by compressing and dilating its basic function. If $a < 1$, the wavelet is compressed and the transformation provides the finer detail of the signal. On the other hand, if $a > 1$, the wavelet is dilated and the transformation provides a coarse view of the signal. In the discrete time circumstance, the wavelet transform can be realized through the implementation of the filter bank tree with high pass filter (HPF) and low pass filter (LPF).

The wavelet coefficients are obtained by passing the input signal, $x(n)$, through the bank of filters as shown in Figure 6 [43]. The wavelet decomposition is achieved where each level is decomposed into approximation and detailed coefficient. The approximate coefficient (CA) is the coefficient corresponding to the low pass filter, whereas the detailed coefficient (CD) is the coefficient corresponding to the high pass filter. The cutoff frequency for each level is the half of the input signal frequency. The signal frequency is then down sampled by 2 for the next level of decomposition which implies the reduction of sampling frequency. The following consecutive decomposition level decomposes the approximate coefficient of the previous level into approximate and detailed coefficients. The signal $f(t)$ can be reconstructed from the wavelet coefficients by applying the inverse wavelet transform.

The advantages of discrete wavelet transform are its linearity, scale covariance, shift covariance, redundancy, zooming, time and frequency localization ability and computational complexity [42, 44]. Besides that, there are numerous types of mother wavelet generally available, such as Haar, Daubechies, Coiflets, Symlets, Biorthogonal, Morlet, Mexican Hat and Meyer. The higher the similarity of the mother wavelet function to the wavelet coefficient of the signal, the more precise the signal of interest can be isolated and identified, to reduce and suppress most of the unwanted noise [32]. Hence, the selection of the mother wavelet function also play an imperative role in the noise reduction application [45]. As a result, the wavelet transform is quickly emerging as a useful tool for noise reduction of the non-stationary signals like ECG and electroencephalogram (EEG) signals because of its advantage and simplicity.

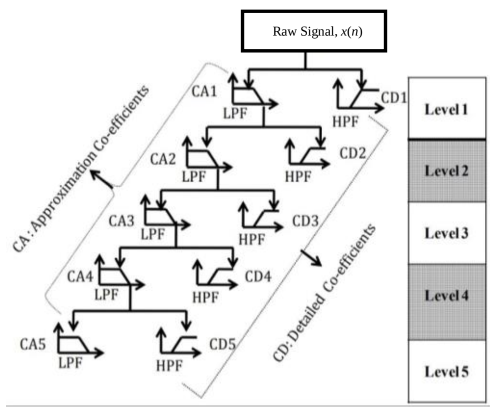


Figure 6. Filter bank structure of the discrete wavelet transform [43].

6. METHODOLOGY

This section presents the methodology of ECG noise reduction and signal enhancement modelling based on various digital filter designs and discrete wavelet decomposition with different mother wavelets. This study applies the ECG-ID Database (*ecgiddb*) which acquired from PhysioNet database as a common dataset to test all ECG noise reduction and signal enhancement methods for quantitative and qualitative performance benchmarking [46, 47]. It consists of 310 sets ECG recording that acquired from 90 subjects, with each record contains 20 seconds ECG lead I signal sampled at the frequency of 500Hz. The *ecgiddb* is chosen in this study instead of the famous MIT-BIH database due to the availability of both raw (Signal 0) and filtered ECG signal (Signal 1) as annotated in PhysioNet database. The raw ECG signal is the noisy ECG signal with the presence of various low and high frequency artifacts and noises. Whereas, the filtered clean ECG signal is the ECG signal that has been filtered and free from noises. The performance benchmarking of various ECG noise reduction methods is based on calculation of Signal-to-Noise Ratio (SNR) and Root Mean Square Error (RMSE) value from 10 sets of randomly selected ECG recording. All the experiments are performed in MATLAB environment.

The ECG noise reduction based on several digital filter designs is first modelled. The selected FIR filter designs are Rectangular Window, Bartlett Window, Hanning Window, Hamming Window, Blackman Window, Blackman-Harris Window and Kaiser Window. On the other hand, the selected IIR filter designs consists of Butterworth, Chebyshev type I, Chebyshev type II and Elliptic filters. The ECG noise reduction algorithm is designed with the combination of high pass filter, low pass filter and notch filter with the aim of reducing and suppressing the unwanted ECG noises.

The order of FIR filters is fixed at 50 whereas the order of IIR filters is fixed at 2. The high pass filter with 0.4Hz cutoff frequency is modelled to reduce and suppress the ECG baseline wandering while avoiding the loss of low frequency ECG information. It is due to the reason that the ECG significant information do present at the frequency of 0.5Hz and above. In addition, the low pass filter with the cutoff frequency of 60Hz is modelled to remove the unwanted high frequency noises. Meanwhile, the notch filter with the cutoff frequency of 50Hz is implemented to remove the powerline interference as the ECG signal obtained from *ecgiddb* databases is distorted by the powerline interference at the frequency of 50 Hz. Furthermore, the passband ripple is set to 1 decibels whereas the stopband ripple is set to 20 decibels for all related filter design such as Chebyshev type I, Chebyshev type II and Elliptic filter designs.

For the discrete wavelet transform modelling to remove unwanted noises incurred during the signal acquisition and transmission process, a raw ECG signal is decomposed into nine levels of decomposition with the discrete wavelet transform. The frequency range of each decomposition level for approximately coefficient and detail coefficient is as shown in Figure 7.

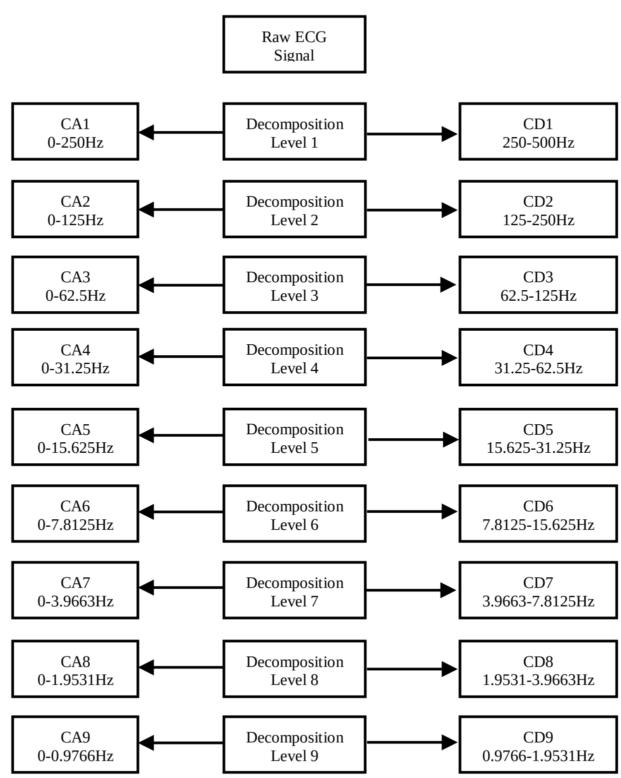


Figure 7. Wavelet decomposition.

Certain wavelet coefficients corresponding to the noises are discarded to suppress and eliminate the unwanted ECG noises. For instance, CA1, CD1, CD2 and CD3 are discarded to eliminate the unwanted high frequency and muscle noises. CA3 and CA9 are also discarded to eliminate the powerline interference and baseline wander noise, respectively. The remaining wavelet coefficients are used to reconstruct the resulting ECG signal by applying the inverse discrete wavelet transform.

In order to search for the most suitable and reliable mother wavelet for the ECG noise reduction and enhancement, the modelling experiment is repeated with different mother wavelets. The selected mother wavelet for investigation in this study includes Daubechies (*db2*, *db3*, *db4*, *db5*, *db6*, *db7*, *db8*, *db9*, *db10*), Coiflets (*coif1*, *coif2*, *coif3*, *coif4*, *coif5*) and Symlets (*sym2*, *sym3*, *sym4*, *sym5*, *sym6*, *sym7*, *sym8*). The selected wavelet families of the Daubechies, Coiflets and Symlets are as shown in Figure 8 [36].

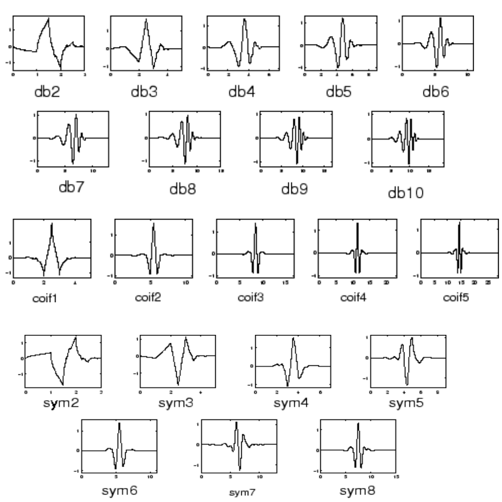


Figure 8. Filter Daubechies (db), Coiflets (coif) and symlets (sym) family wavelets [36].

Lastly, the performance of the ECG noise reduction method based on various digital filters and the discrete wavelet transform with different mother wavelets are analyzed and compared in terms of SNR and RMSE measurement. SNR is defined as the ratio of signal power to noise power as expressed in equations (24) and (25), respectively, which indicates the quality of signal. The higher the SNR value represents the better the quality of the signal, as well as better efficiency of the ECG noise reduction and signal enhancement method. The ECG noise can be estimated by subtracting the filtered ECG signal from the raw ECG signal as both of them are available in *ecgiddb* database. Besides that, RMSE is used to measure the distortion of the noise reduction and signal enhancement process. The smaller the RMSE value is, the lesser the distortion of the signal after the noise reduction process and closer to the noiseless signal. The mathematical definition of RMSE is expressed in (26).

$$SNR = P\_signal/P\_noise \tag{24}$$

$$SNR_{dB} = 10log_{10}(SNR) \tag{25}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}[s(n) - s^*(n)]^2} \tag{26}$$

where $s(n)$ is the noiseless ECG signal and $s^*(n)$ is the de-noised ECG signal.

In brief, the larger SNR value and the smaller RMSE value indicate a dedicated ECG noise reduction and enhancement method have better performance in reducing and suppressing the ECG unwanted noises, while good in preserving the significance ECG characteristics, such as P, QRS and T waves. The performance of ECG noise reduction and signal enhancement method based on different digital filter designs and various mother wavelet functions are therefore can be fairly evaluated and benchmarked to each other. This aims to identify the most suitable digital filter design and mother wavelet function for processing a raw ECG signal. Moreover, the SNR and RMSE value are calculated before and after the noise reduction and enhancement process to measure the effectiveness and reliability of the selected methods.

7. EXPERIMENTAL RESULTS AND EVALUATION

In this section, the experimental results and performance evaluation of the ECG noise reduction and enhancement method based on various digital filter designs and discrete wavelet transform based on various mother wavelets are presented and discussed. The total of 10 sets raw ECG recordings are randomly selected from the *ecgiddb* database which acquired from PhysioNet [43, 44] are used to evaluate, compare and benchmark the ECG noise reduction and enhancement methods. The significance of ECG noise reduction and enhancement method is measured by means of obtaining the higher SNR and minimal RMSE value. The SNR and RMSE value for the raw ECG datasets and its average value are shown in Table I. Meanwhile, the quality of the ECG signal is evaluated and compared by averaging both SNR and RMSE value after processed with various digital filter designs based ECG noise reduction and enhancement method for ten datasets used as shown in Table II.

Form Table I and II, the experimental results shown that the ECG signal do improved after the ECG noise reduction and enhancement process based on both FIR and IIR digital filter designs. Among various FIR digital filter designs, the rectangle window achieves the highest average SNR value with 0.5397 and lower average RMSE value with 76.9816 compared to other FIR digital filter designs. However, the performance of the FIR digital filter designs and signal quality improvement still remain insignificant by comparing their average SNR and RMSE value before and after noise reduction and enhancement process.

TABLE I. SNR AND RMSE FOR THE RAW ECG DATASETS AND ITS AVERAGE VALUE

Dataset Name	Dataset label	SNR	RMSE
Person_02	Data 1	-0.3131	43.1255
Person_03	Data 2	-0.4772	67.1515
Person_05	Data 3	-0.0431	164.6364
Person_06	Data 4	-0.2819	42.4304
Person_08	Data 5	-0.0297	284.555
Person_09	Data 6	-0.7489	38.7486
Person_10	Data 7	-0.8661	39.6826
Person_11	Data 8	-0.3391	36.5351
Person_13	Data 9	-0.0651	84.1185
Person_16	Data 10	-1.3147	28.3782
Average value		-0.44789	82.93618

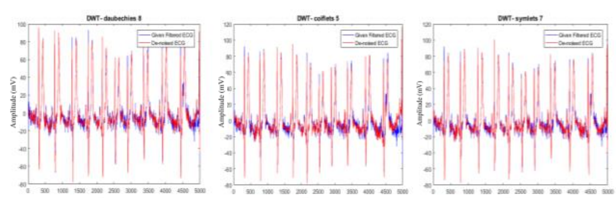
TABLE II. AVERAGE SNR AND RMSE VALUE AFTER ECG NOISE REDUCTION AND ENHANCEMENT PROCESS BASED ON VARIOUS DIGITAL FILTER DESIGNS

Digital Filter	Average	
	SNR	RMSE
Least Square	0.0592	85.4115
Constrained Least Square	0.0432	84.9333
Rectangular Window	0.5397	76.9816
Bartlett Window	-0.1874	89.0911
Hanning Window	0.0077	85.5842
Hamming Window	0.0508	84.854
Blackman Window	-0.0176	85.9844
Blackman-Harris Window	-0.0485	86.5241
Kaiser Window	0.5141	77.3811
Butterworth	4.7327	7.7629
Chebyshev type I	5.4995	8.7724
Chebyshev type II	4.9548	7.8074
Elliptic	5.4861	9.2758

As aforementioned, the negative SNR value signifies that the signal consists a lot of noises as the noise power is greater than the signal power, while the large RMSE signifies the large distortion after noise reduction and enhancement process. The experimental results are verified with the visual comparison between the filtered noiseless ECG signal which provided by the *ecgiddb* database and de-noised ECG signal obtained after the ECG noise reduction and enhancement process as shown in Figure 9. All the visual comparison is based on the ECG dataset data 6 as an illustration example.

Besides that, the ECG noise reduction and enhancement method based on IIR digital filter designs achieve much optimize performance in term of average SNR and RMSE value. The Chebyshev type I achieve higher average SNR value with 5.4995, while the Butterworth is having the lowest average RMSE value with 7.7629 among the IIR digital filter designs. This indicates that the ECG noise reduction method based on IIR digital filter designs outperforms the FIR digital filter designs and achieve more significant performance in eliminating the unwanted ECG noise distortion which can be visualized in Figure 9. Furthermore, the average SNR and RMSE value for ten ECG datasets after processing with the noise reduction and enhancement method based on discrete wavelet transform with 22 different mother wavelet functions are shown in Table 3.

Among 22 mother wavelets, *db8*, *coif5* and *sym7* have obtained the best ECG noise reduction and enhancement performance by achieving lower RMSE value within their wavelet family. The resulting ECG signal after noise reduction and enhancement with *db8*, *coif5* and *sym7* can be visualized in Figure 10.



(a) (b) (c)

Figure 10. Visual comparison between the noiseless ECG signal (blue) which provided by the *ecgiddb* database and de-noised ECG signal (red) obtained after ECG noise reduction based on discrete wavelet transform with mother wavelet of *db8*, *coif5* and *sym7*.

8. CONCLUSION

In this study, the quantitative and qualitative performance comparison and benchmarking of the ECG noise reduction and signal enhancement methods based on various digital filter designs and mother wavelets using common *ecgiddb* database have been clearly presented.

The experimental result shows that the IIR digital filter can greatly reduce the noises and able to retain the significance ECG morphology features effectively. It can be concluded that the IIR digital filter designs outperform the FIR digital filter designs in ECG noise reduction and signal enhancement.

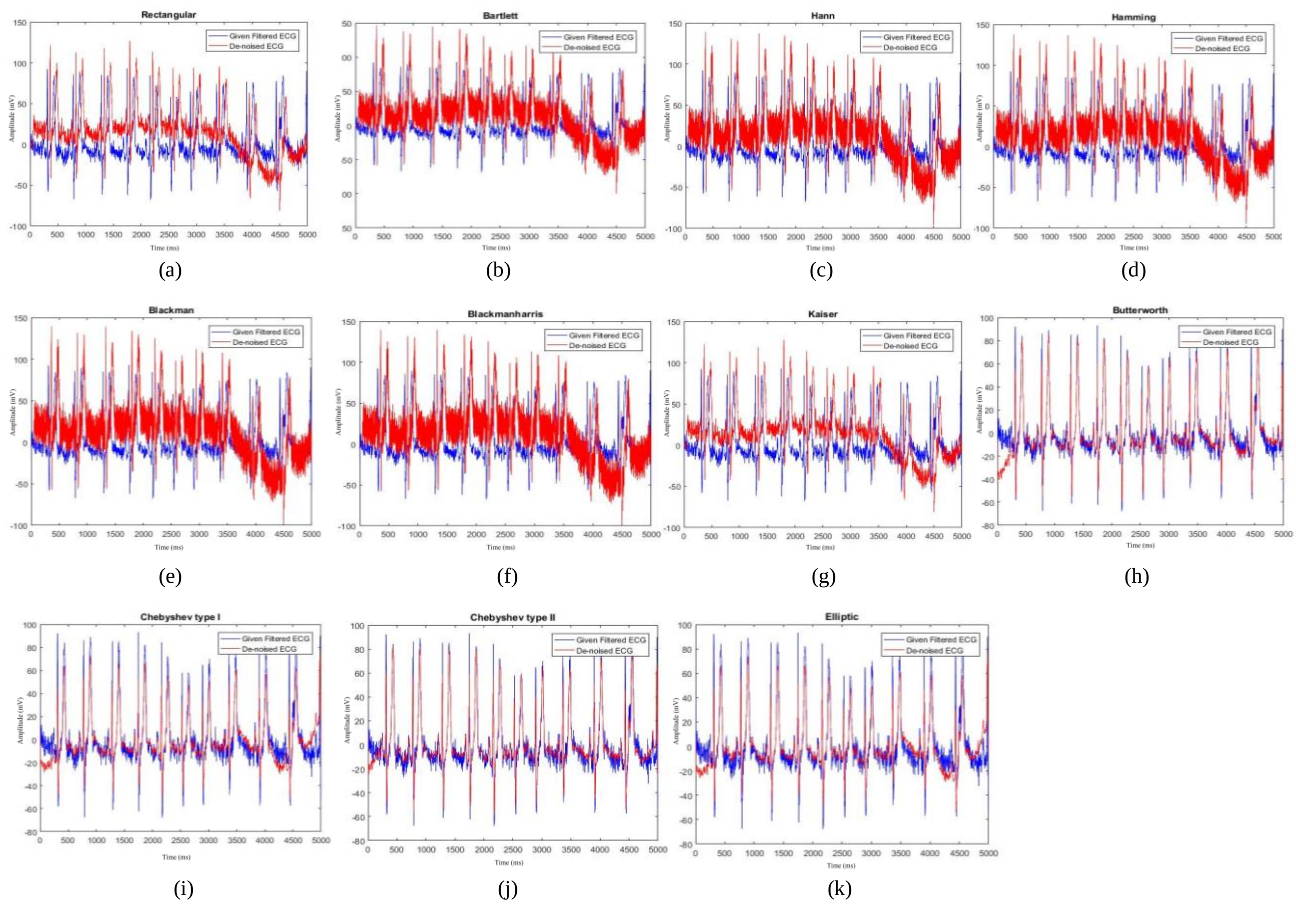


Figure 9. Visual comparison between the noiseless ECG signal (blue) which provided by the ecgiddb database and de-noised ECG signal (red) obtained after ECG noise reduction and enhancement based on various FIR and IIR digital filter designs.

This can be observed qualitatively and quantitatively as the FIR digital filter designs are unable to effectively suppress and remove the unwanted ECG noises, such as the powerline interference, baseline wander and high frequency noises, even though the filter order is set to 50. Besides that, FIR digital filter designs also cause serious issue of phase shifting due to its larger filter order. Its performance also reflected by the lower SNR and higher RMSE value quantitatively in comparison with IIR filters. On the other hand, the phase shifting or delay of the IIR filter designs are approximately zero, hence it is tolerable. Moreover, it is a computational effective approach as it only requires the filter order of 2.

Nevertheless, the ECG noise reduction and signal enhancement methods based on IIR digital filter still suffers from suppressing and removing the unwanted noises that lies within the similar frequency range with the significant ECG morphology features, such as electrode motion noise and electromyography noise. This can be solved by using the discrete wavelet transform which analyze an ECG signal in both time and frequency domain. The selection of proper mother wavelets does influence the performance and efficiency of the ECG noise reduction and enhancement method. Lastly, this article has highlighted the contribution by presenting a structured qualitative and quantitative analysis of the ECG noise reduction and signal enhancement method based on various digital filter designs and the discrete wavelet transform with various mother wavelets using common dataset for systematic performance benchmarking. It is hoped that the advanced ECG noise reduction and signal enhancement method based on artificial intelligence or machine learning could further assist the accurate ECG signal analysis in detecting, predicting and diagnosing the cardiac abnormalities and life-threatening diseases.

TABLE III. AVERAGE SNR AND RMSE AFTER ECG NOISE REDUCTION AND ENHANCEMENT PROCESS BASED ON VARIOUS MOTHER WAVELET FUNCTIONS

Mother wavelets	**Average Value**	
	SNR	**RMSE**
db1	4.35497	10.58172
db2	4.42932	7.84888
db3	4.38736	6.28766

db4	4.41898	4.90001
db5	4.44123	5.21812
db6	4.43808	5.56058
db7	4.42493	5.0377
db8	4.41481	4.07699
db9	4.42838	4.87475
db10	4.41376	5.53935
coif 1	4.38822	7.18038
coif 2	4.41365	5.37712
coif 3	4.42372	5.03287
coif 4	4.41636	4.69886
coif 5	4.42444	4.66161
sym2	4.42932	7.84988
sym3	4.38736	6.28766
sym4	4.40788	5.14143
sym5	4.4466	5.94994
sym6	4.40928	4.81891
sym7	4.43083	4.39965
sym8	4.41427	4.78434

ACKNOWLEDGMENT

This research is fully supported and funded by the Ministry of Higher Education (MoHE) Trans-Disciplinary Research Grant Scheme (TRGS) with Grant no. TRGS/1/2015/UTM/02/3/3 (UTM vote no. R.J130000.7845.4L842) and Universiti Teknologi Malaysia through the sponsorship of Zamalah UTM.

REFERENCES

[1] W.H Organization, "World Health Statistics 2018: Monitoring health for the SDGs. " 2018.

[2] Al-Mawali, A., "Non-communicable diseases: shining a light on cardiovascular disease", Oman's biggest killer. Oman medical journal, vol 30(4) pp. 227, 2015.

[3] W.H Organization, "Global Status Report on Noncommunicable Diseases. Geneva: World Health Organization", 2010.

[4] Benjamin, E.J., et al., "Heart Disease and Stroke Statistics-2017 Update:" A Report From the American Heart Association. Circulation, vol. 135(10): pp. e146-e603, 2017.

[5] Kumar, S., "Cardiovascular Disease and Its Determinants: Public Health Issue." J Clin Med Ther, vol. 1: pp. 1, 2016.

[6] Pandit, D., et al., "Noise Reduction in ECG Signals Using Wavelet Transform and Dynamic Thresholding", in Emerging Trends in Neuro Engineering and Neural Computation. Springer. p. 193-206, 2017.

[7] Qureshi, S., et al., "Noise reduction of electrocardiographic signals using wavelet transforms." Elektronika ir Elektrotechnika, vol. 20(4): p. 39-42, 2014.

[8] Luo, S. and P. Johnston, "A review of electrocardiogram filtering." J Electrocardiol, vol. 43(6): p. 486-96, 2010.

[9] Kaur, M. and G. Kaur, "Adaptive wavelet thresholding for noise reduction in electrocardiogram (ECG) signals," International Journal of Computer Science and Network Security (IJCSNS), vol. 15(4): p. 100, 2015.

[10] Limaye, H. and V. Deshmukh, "ECG noise sources and various noise removal techniques: a survey," International Journal of Application or Innovation in Engineering & Management, vol. 5(2): p. 86-92, 2016Maggio, A.C.V., et al., "Quantification of Ventricular Repolarization Dispersion Using Digital Processing of the Surface ECG," in Advances in Electrocardiograms-Methods and Analysis. 2012, InTech.

[11] Bates, R., et al., "The ATLAS SCT grounding and shielding concept and implementation," Journal of Instrumentation, vol. 7(03): p. P03005, 2012.

[12] Shirbani, F. and S.K. Setarehdan. "ECG power line interference removal using combination of FFT and adaptive non-linear noise estimator," in Electrical Engineering (ICEE), 2013 21st Iranian Conference on. 2013.

[13] Chavan, M.S., R. Agarwala, and M. Uplane, "Suppression of baseline wander and power line interference in ECG using digital IIR filter," International journal of circuits, systems and signal processing, vol. 2(2): p. 356-365, 2008.

[14] Sayadi, O. and M.B. Shamsollahi, "Multiadaptive bionic wavelet transform: Application to ECG denoising and baseline wandering reduction," EURASIP Journal on Advances in Signal Processing, vol. 2007(1): p. 041274, 2007.

[15] Tasa, B.P., et al., "Simulation Based R-peak and QRS complex detection in ECG Signal," Current Trends in Technology and Science, vol. 2(4): p. 277-282, 2013.

[16] Jané, R., et al. "Adaptive baseline wander removal in the ECG: Comparative analysis with cubic spline technique," Proceedings in Computers in Cardiology 1992, IEEE

[17] Subramaniam, S.R., B.W.-K. Ling, and A. Georgakis. "Motion artifact suppression in the ECG signal by successive modifications in frequency and time," in Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE. 2013. IEEE

[18] Yapici, M.K. and T.E. Alkhidir, "Intelligent medical garments with graphene-functionalized smart-cloth ECG sensors," Sensors, vol. 17(4): p. 875, 2017.

[19] Christov, I.I. and I.K. Daskalov, "Filtering of electromyogram artifacts from the electrocardiogram," Medical Engineering and Physics, vol. 21(10): p. 731-736, 1999.

[20] Abbaspour, S. and A. Fallah, "Removing ECG Artifact from the surface EMG signal using adaptive subtraction technique," Journal of biomedical physics & engineering, vol. 4(1): p. 33, 2014.

[21] Willigenburg, N.W., et al., "Removing ECG contamination from EMG recordings: A comparison of ICA-based and other filtering procedures," Journal of electromyography and kinesiology, vol. 22(3): p. 485-493, 2012.

[22] Viitasalo, J.H. and P.V. Komi, "Signal characteristics of EMG during fatigue," European Journal of Applied Physiology and Occupational Physiology, vol. 37(2): p. 111-121, 1977.

[23] Merletti, R. and P. Di Torino, "Standards for reporting EMG data," J Electromyogr Kinesiol, vol. 9(1): p. 3-4, 1999.

[24] Van Boxtel, A., "Optimal signal bandwidth for the recording of surface EMG activity of facial, jaw, oral, and neck muscles," Psychophysiology, vol. 38(1): p. 22-34, 2001.

[25] Marouf, M., L. Saranovac, and G. Vukomanovic, "Algorithm for EMG noise level approximation in ECG signals," Biomedical Signal Processing and Control, vol. 34: p. 158-165, 2017.

[26] T. M. Chieng, Y. W. Hau and Z. Omar, "The Study and Comparison between Various Digital Filters for ECG De-noising," 2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES), Sarawak, Malaysia, 2018, pp. 226-232. doi: 10.1109/IECBES.2018.8626661

[27] Xiong, P., Wang, H., Liu, M., Zhou, S., Hou, Z., and Liu, X. "ECG signal enhancement based on improved denoising auto-encoder," Engineering Applications of Artificial Intelligence, vol. 52: p. 194-202, 2016.

[28] Antczak, K. "Deep recurrent neural networks for ECG signal denoising," arXiv preprint arXiv:1807.11551, 2018.

[29] Arsene, C. T., Hankins, R., and Yin, H. "Deep Learning Models for Denoising ECG Signals," 2019 27th European Signal Processing Conference (EUSIPCO), 2019, pp. 1-5: IEEE.

[30] Nagendra, H., S. Mukherjee, and V. Kumar, "Wavelet based nonlinear thresholding techniques for pre-processing ECG signals," International Journal of Biomedical and Advance Research, vol. 4(8): p. 534-544, 2013.

[31] Rahman, M.W. and M.A. Riheen. "Compatibility of mother wavelet functions with the electrocardiographic signal," in Informatics, Electronics & Vision (ICIEV), 2013 International Conference on. 2013. IEEE.

[32] Rangayyan, R.M., "Biomedical Signal Analysis," 2015: Wiley.

[33] Kemppainen, R., "ECG Parameters in Short-Term Prediction of Ventricular Arrhythmias," 2012.

[34] Sampson, M. and A. McGrath, "Understanding the ECG. Part 1: Anatomy and physiology," British Journal of Cardiac Nursing, 2015. 10(11): p. 548-554.

[35] Peng, S., "Design and analysis of FIR filters based on Matlab," 2013.

[36] Losada, R.A., "Digital filters with MATLAB," The MathWorks, Inc, 2008.

[37] Prabhakar, S. and A.S. Sappal, "Transition Bandwidth Analysis of Infinite Impulse Response Filters."

[38] Matlab Documentation, The MathWorks Inc. 2005.

[39] Mallat, S.G., "A theory for multiresolution signal decomposition: the wavelet representation," IEEE transactions on pattern analysis and machine intelligence, vol. 11(7): p. 674-693, 1989.

[40] Alfaouri, M. and K. Daqrouq, "ECG signal denoising by wavelet transform thresholding," American Journal of applied sciences, vol. 5(3): p. 276-281, 2008.

[41] Kumar, A. and M. Singh, "Robust Multiresolution Wavelet Analysis and Window Search Based Approach for Electrocardiogram Features Delineation," Journal of Medical Imaging and Health Informatics, vol. 6(1): p. 146-156, 2016.

[42] Karthikeyan, P., M. Murugappan, and S. Yaacob, "ECG signal denoising using wavelet thresholding techniques in human stress assessment," International Journal on Electrical Engineering and Informatics, vol. 4(2): p. 306, 2012.

[43] Graps, A., "An introduction to wavelets. IEEE Computational Science and Engineering," vol. 2(2): p. 50-61, 1995.

[44] Rafiee, J., et al., "Wavelet basis functions in biomedical signal processing," Expert systems with Applications, vol. 38(5): p. 6190-6201, 2011.

[45] Lugovaya, T.S., "Biometric human identification based on ECG," PhysioNet, 2005.

[46] Goldberger, A.L., "PhysioBank, PhysioToolkkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals," Circulation, vol. 101(23): p. e215-e220, 2000.

Thion Ming Chieng is pursuing Ph.D. degree in biomedical engineering from Universiti Teknologi Malaysia. He obtained his Master's degree in Biomedical Engineering and Bachelor's degree in Microelectronic Engineering from Universiti Teknologi Malaysia. His research interests are in medical image processing and medical signal processing.

Dr. Yuan Wen Hau is as a research fellow and the head of Cardiac Informatics Cluster at UTM-IJN Cardiovascular Engineering Centre, Universiti Teknologi Malaysia. She is also a senior lecturer at the School of Biomedical Engineering and Health Sciences, Faculty of Engineering, Universiti Teknologi Malaysia. She received both Ph.D. degree and Master's degree in Electrical Engineering from Universiti Teknologi Malaysia in 2009 and 2005, respectively. Dr. Hau's research interests are in the design of multi-processor systems-on-chip (MPSoC) /networks-on-chip (NoC), from electronic system level (ESL) modelling to Register Transfer Level (RTL), as well as field programmable gate array (FPGA) implementation. From there her research interests have spread into the field of cryptographic and data security application, biomedical application such as arrhythmia classification and medical imaging processing, as well as ADHD/autism assessment. She has published more than 30 papers in peer reviewed international journals and conferences, and several book chapters. She is also a member of the IEEE.

Dr. Zaid Bin Omar and a short biography is a senior lecturer at the School of Electrical Engineering, Universiti Teknologi Malaysia. He completed his PhD at Imperial College London in 2012, where he worked on fusion algorithms of digital images, and his Master's degree was from the University of Sheffield in 2008. Prior to that, Dr. Zaid was an engineer with a security consultancy firm in Kuala Lumpur. He obtained his Bachelor's degree in Computer Engineering from UTM in 2006. Dr. Zaid's primary research interests are in digital image processing, medical imaging and artificial intelligence. He holds several research grants and has close collaborations with Malaysia's Institut Jantung Negara (IJN). He has published numerous works in the field and is currently a supervisor to several postgraduate students. Presently, Dr. Zaid is seconded to the Ministry of Education Malaysia, where he heads the Students Development Office.

Dr. Chiao Wen Lim is a senior lecturer and acting consultant cardiologist at Universiti Teknologi MARA (UiTM). She is currently the coordinator of clinical services of the Department of Cardiology in UiTM. She obtained her MRCP (UK) in 2011 and her undergraduate medical degree from University of Glasgow in 2007. Dr. Lim's special interest is in the field of cardiac electrophysiology and syncope. She pursued her fellowship training in cardiac electrophysiology in London in 2016 to 2018.

International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 9, No.4 (July-2020)

E-mail: billy5392@gmail.com, hauyuanwen@biomedical.utm.my, zaid@fke.utm.my, chiaowen.lim@gmail.com